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Zeren Li

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Keywords: Favoritism; Political Risks; Government Procurement; Anticorruption Campaign; China

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Zeren Li †
Songrui Liu ‡
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†The Whitney and Betty Macmillan Center for International and Area Studies, Yale University, zeren.li@yale.edu.

‡China Center for Economic Research, National School of Development, Peking University, srliu2018@nsd.pku.edu.cn.

Public goods distribution is never free from political favoritism. Politicians around the world tend to show bias toward certain regions, individuals, and business groups when distributing public resources (Golden and Min, 2013). A widely known theoretical explanation for political favoritism is electoral concerns: politicians distribute benefits to targeted citizens or business groups in exchange for votes or campaign contributions (Fouirnaies and Mutlu-Eren, 2015; Boas, Hidalgo and Richardson, 2014). Political favoritism is even more rampant in authoritarian countries. In contexts lacking meaningful representation, political leaders with strong incentives for career advancement provide preferential treatment to firms that can directly increase their career prospects (Jensen and Malesky, 2018; Chen and Kung, 2019; Chen and Zhang, 2021).

We advance the established literature on distributive politics under authoritarian regimes. Instead of focusing on career advancement incentives, our paper centers on a key feature of authoritarian rule: a high-risk environment characterized by the possibility of unexpected political turnovers such as coups and purges (Gandhi and Przeworski, 2007; Svolik, 2012). We argue that the uncertain political environment leads to a form of risk-driven favoritism. When political risks surge, officials shift their concerns from seeking political and pecuniary rents to maintaining political power. This rent–survival trade-off manifests in the distribution of public resources. Because of the dominance of survival concerns, officials distribute favors disproportionately to state-affiliated economic agents rather than to private firms because such allocations are less prone to arousing suspicions of political offenses that could cost them their political careers. As the favor toward state-owned enterprises (SOEs) is driven by political calculus, it introduces resource allocation distortions at the expense of efficiency.

We document this risk-driven favoritism by focusing on China's government procurement process, whereby public agencies acquire goods and services by contracting with firms. Government procurement is a crucial setting for examining favoritism in distributive politics because of its scale and salience. Around the world, the size of government procurement is tremendous, reaching \$11 trillion US dollars in 2018 and amounting to 12% of global GDP (Bosio et al., 2022). In China, public procurement has also become a substantial part of the economy since related legislation was passed in 2003. In 2018, the gross value of procurement contracts in China reached 3.58 trillion yuan (0.52 trillion US dollars), accounting for approximately 3.9% of GDP and 16.2% of public expenditure.[1]

We empirically estimate risk-driven favoritism in public procurement by drawing on various data sources. We first use various machine learning algorithms to assemble an original Chinese Government Procurement Database (CGPD). The CGPD includes detailed information on all procurement contracts disclosed by the Chinese government since 2008. We then match the CGPD with all 2,878 firms publicly listed on the Chinese stock market from 2008 through 2018. We define state affiliation in this paper by focusing on firms' ownership structure, viewing SOEs as regime insiders, as China's party state supervises their performance, controls their personnel, and invests in their equity.

Our empirical analysis leverages the anticorruption campaign launched in late 2012, which creates exogenous variation in the career uncertainty faced by officials. Before showing the results of quantitative analyses, we demonstrate the existence of risk-driven favoritism using qualitative interviews with government procurement agencies, firm managers, and local officials in China.[2] The cases show that officials are more inclined to provide favors to SOEs, thereby reducing their career risks because such allocations do not imply corruption. To examine the generalizability of the risk-driven favoritism observed in the case studies, our quantitative analysis documents the changes in the SOE premium, measured by the difference in the volume and value of procurement contracts between SOEs and non-SOEs, before and during the campaign. The firm-level estimation shows a salient effect of officials' survival concerns on government procurement. The SOE premium in the volume and value of procurement contracts increased by approximately 20% and 52%, respectively, in the wake of the campaign. A back-of-the-envelope estimation shows that the gross SOE premium is approximately 194.4 billion yuan (28.6 billion US dollars) over the first six years' of the campaign, a tremendous size that is close to the GDP of Nepal. We fur-

[1] Here public expenditure refers to the national general public budget expenditure (yi ban gong gong yu suan zhi chu).

[2] The interviews were granted approval from the institutional review board.

ther demonstrate that the SOE premium is driven by political risks by focusing on within-campaign variation. Using a province-by-firm-by-year dyadic analysis, we show that provincial governments under roving inspections, a draconian anticorruption measure imposed by the party center, provide significantly more procurement to SOEs than to non-SOEs. Beyond showing evidence on the political risk mechanism, we provide evidence that excludes several alternative explanations including corporate performance, local policy trends, fiscal burden, and geopolitical tensions.

We then show evidence of the efficiency losses from such allocations by analyzing the productivity consequences for firms. Our ex ante analysis shows declining quality among winning bidders since the start of corruption crackdown. We also conduct an ex post analysis of how favorable government contracts affect firm productivity. Again, the evidence suggests that the anticorruption campaign reduced public procurement allocation efficiency. Our firm-level estimation shows that the productivity gap between SOEs and non-SOEs further deepened significantly during the corruption crackdown.

By documenting the rising SOE premium and the associated efficiency losses, this paper mainly contributes to a growing body of literature on the distributive politics of government procurement. Research shows that lucrative procurement contracts are either a form of bribe or a means for politicians to seek electoral victories (Boas, Hidalgo and Richardson, 2014; Auriol, Straub and Flochel, 2016; Klašnja, 2015; Coviello and Gagliarducci, 2017). We complement the research on political favoritism by documenting a political survival mechanism. We follow a burgeoning stream of literature that highlights the role of survival concerns in public policy decisions under authoritarian rule (Li, Li and Zhang, 2023; Hou and Li, 2022). More importantly, we not only estimate the size of this risk-driven favoritism but also demonstrate the associated efficiency losses and considerable costs to public welfare, suggesting the distortionary nature of political favoritism.

Risk-Driven Favoritism in Public Resource Allocation

This study theoretically and empirically analyzes political favoritism, preferential treatment provided by political leaders to certain segments of citizens in authoritarian regimes. The existing scholarship shows that politicians disproportionately distribute public resources to their birthplace regions (e.g., Hodler and Raschky, 2014), coethnic groups (e.g., Kramon and Posner, 2016), and clan members (e.g., Do, Nguyen and Tran, 2017). The biased distribution of public resources manifests in various aspects, including extra public goods provision (Burgess et al., 2015), favorable taxation (Kasara, 2007), and public employment (Baskaran and da Fonseca, 2021). A prevailing explanation for political favoritism is electoral concerns. Facing strong political competition, electoral leaders favor their core or swing voters to garner support. After winning elections, they give favorable procurement contracts to their campaign donors (Boas, Hidalgo and Richardson, 2014). Electoral concerns also affect the timing of favors, which usually are given before elections, thereby leading to political budget cycles (Shi and Svensson, 2006; Min and Golden, 2014).

While it is widely documented that elected leaders favor certain groups of citizens or businesses given their career concerns, political favoritism also characterizes nonelectoral contexts, including authoritarian countries that lack competitive elections.[3] Political favoritism is viewed mainly as a means of seeking economic and political rents. Corruption scholars contend that political leaders subject to weak institutional constraints use their discretion to favor businesses aligned with their pecuniary interests (Bardhan, 2017). Moreover, political leaders advance their career prospects by favoring targeted social and business groups. Mounting evidence on single-party regimes documents such political rent-seeking activities in public resource allocation. For example, in Vietnam, local leaders strategically allocate benefits to firms that can help them signal competence in the critical years of their political careers (Jensen and Malesky, 2018). In China, political leaders favor firms with ties to their political patrons who decide their promotion (Chen and Kung, 2019).

Beyond the rent-seeking mechanism, an understudied mechanism that could account for po-

[3]Political favoritism also appears in the bureaucratic process in advanced democracies, including the government procurement process (e.g., Dahlström, Fazekas and Lewis, 2021; Broms, Dahlström and Fazekas, 2019).

litical favoritism in nondemocracies is political survival. As a distinctive feature of authoritarian rule, authoritarian leaders are subject to high career uncertainties—they are likely to experience unexpected political turnovers caused by coups, purges, and even assassinations (Gandhi and Przeworski, 2007; Svolik, 2012). In such a high-risk environment, the dominant political objective of officials is to minimize the cost of political errors rather than to maximize their opportunities for rent-seeking. Our study analyzes this risk-driven decision-making in the government procurement context, where officials distribute public funds to firms for public goods delivery. We argue that risk-driven favoritism manifests in a dynamic manner. When their political status is stable, officials distribute more contracts to firms that can help them advance their political careers or economically enrich themselves. However, when external political risks increase, they reduce their effort in rent-seeking activities that may cost them their political careers. Instead, they distribute benefits to firms that can secure their political survival.

We theorize that this trade-off between rent-seeking and political survival is reflected in the bias related to firms' ownership type.[4] In particular, political favors shift from private firms to SOEs. When perceived career risk is low, officials do business with private firms. A career concern explanation is that private firms are more efficient than SOEs in generating revenue and profits and therefore that allocating resources to private firms helps politicians signal competence. Moreover, in a weak institutional context lacking property rights protection, private firms often bribe political leaders in exchange for protection and favors, making them money bags for corrupt politicians. However, faced with increased career uncertainties, political leaders shift their priority from these rent-seeking activities to political survival. We expect that to maintain their power, officials tend to contract with SOEs, as they are safer choices in an uncertain environment for two reasons. First, SOEs are state-affiliated agents that have ties with upper-level government or serve as local selectorates. Providing benefits to SOEs may help officials garner internal political support, thereby advancing their survival in office. Moreover, distributing benefits to SOEs does not involve political errors. While making deals with private firms may imply corruption, doing business with

[4] In the financial market, information on firm ownership is publicly available to officials for their decision-making because of information disclosure rules.

SOEs is less likely to be viewed as an illicit exchange of favors that could cost officials their political careers. Given the fixed public resources at officials' disposal, we expect political favors to shift from private firms to SOEs when officials face higher career risks. Based on these arguments, we develop our main hypothesis as follows.

Risk-driven favoritism: When career risks increase, officials provide more favors to state-owned enterprises when allocating government resources.

The High-Risk Environment

We empirically document risk-driven favoritism using the case of the anticorruption campaign in China. We characterize the campaign in China as a high-risk environment. In late 2012, Xi Jinping launched an unprecedentedly massive anticorruption campaign, commanded by the Central Commission for Discipline Inspection (CCDI). The defining features of this campaign are its scope and intensity. Over the first five years of the campaign, the party's anticorruption agencies have investigated over 1.5 million officials (Gan and Choi, 2018). More importantly, the campaign is a political shock targeting officials at various ranks from top to bottom, including the CPC's former law enforcement tsar Zhou Yongkang and tens of thousands of entry-level civil servants.

As a major effort of the campaign, the CCDI sent its Central Inspection Team (CIT) to all 31 provincial units, central government agencies, and public institutions to conduct investigations against corruption. Figure A.1 shows the timeline of the provincial-level inspections. These inspections deliver tremendous political shocks to local leaders because they increase exposure of corruption activities. According to a report by the CCDI in late 2017, over 60% of corruption cases have been revealed through these inspections.[5] The shocking effect of CIT inspections spreads even to lower-level governments in the inspected province. In some extreme cases, local leaders have even sent officials to prevent aggrieved citizens from approaching the inspection team's hotel.[6]

[5] http://m.ccdi.gov.cn/content/98/f8/20269.html

[6] http://cpc.people.com.cn/n/2014/0414/c371963-24893710.html

Because of its high intensity, the anticorruption campaign has increased the career risks faced by local officials, affecting their decision-making in various ways. Political leaders who are surrounded by corruption dismissals promote less connected subordinates to avoid giving the impression of forming factions, which is considered a major political offense under Xi Jinping's rule (Li and Manion, 2022). Provincial leaders are less inclined to promote their internal agency or local subordinates to avoid accusations of political wrongdoing or of attempting to assert local control (Wang, 2022*b*; Juan and Tang, Forthcoming). Beyond its impact on political selection, the draconian crackdown has affected decision-making on economic policies. Fears of corruption dismissals discourage officials from selling land to private firms, collecting revenue or conducting environmental inspections (Fang et al., 2022; Wang and Dickson, 2022). Our study extends previous analyses of the chilling effect of corruption crackdowns on the distribution of public procurement. In the next section, we describe the mechanics of the procurement process and show various ways through which local officials use their discretion to interfere with procurement allocation when faced with career risks.

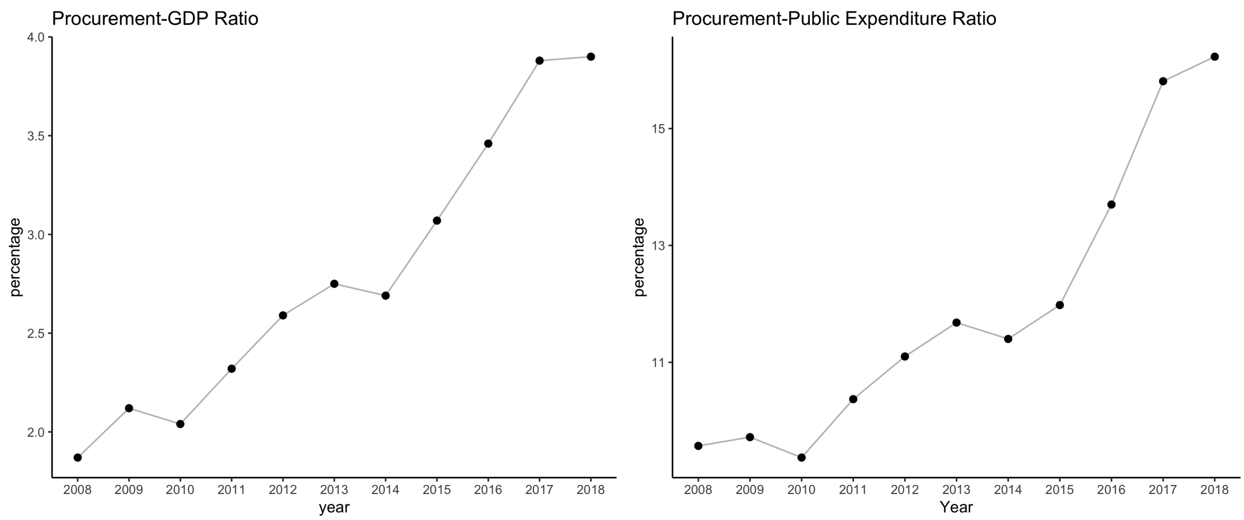
Government Procurement in China

Since the passing of the Government Procurement Law in 2003, the size of government procurement has grown rapidly in China. Figure 1 shows a constant increase in the value of government procurement as a ratio to GDP and public expenditure in China from 2008 to 2018. In 2018, government procurement reached a record high of 3.58 trillion yuan, accounting for 16.2% and 3.9% of public expenditure and GDP, respectively. The main procurers in these government contracts are local governments, which account for over 90% of the procurement value.

Government procurement in China has a standardized procedure, as shown by the diagram in Figure 2. In general, there are five common ways through which a firm obtains a procurement contract. The most common method is open bidding. Government agencies must use the open bidding method if the budget exceeds a certain amount.[7] Otherwise, government agencies can use four

[7]For example, in Zhejiang Province, the value threshold for open bidding was 1 million yuan in 2018. See

Figure 1: Time Trend of Government Procurement



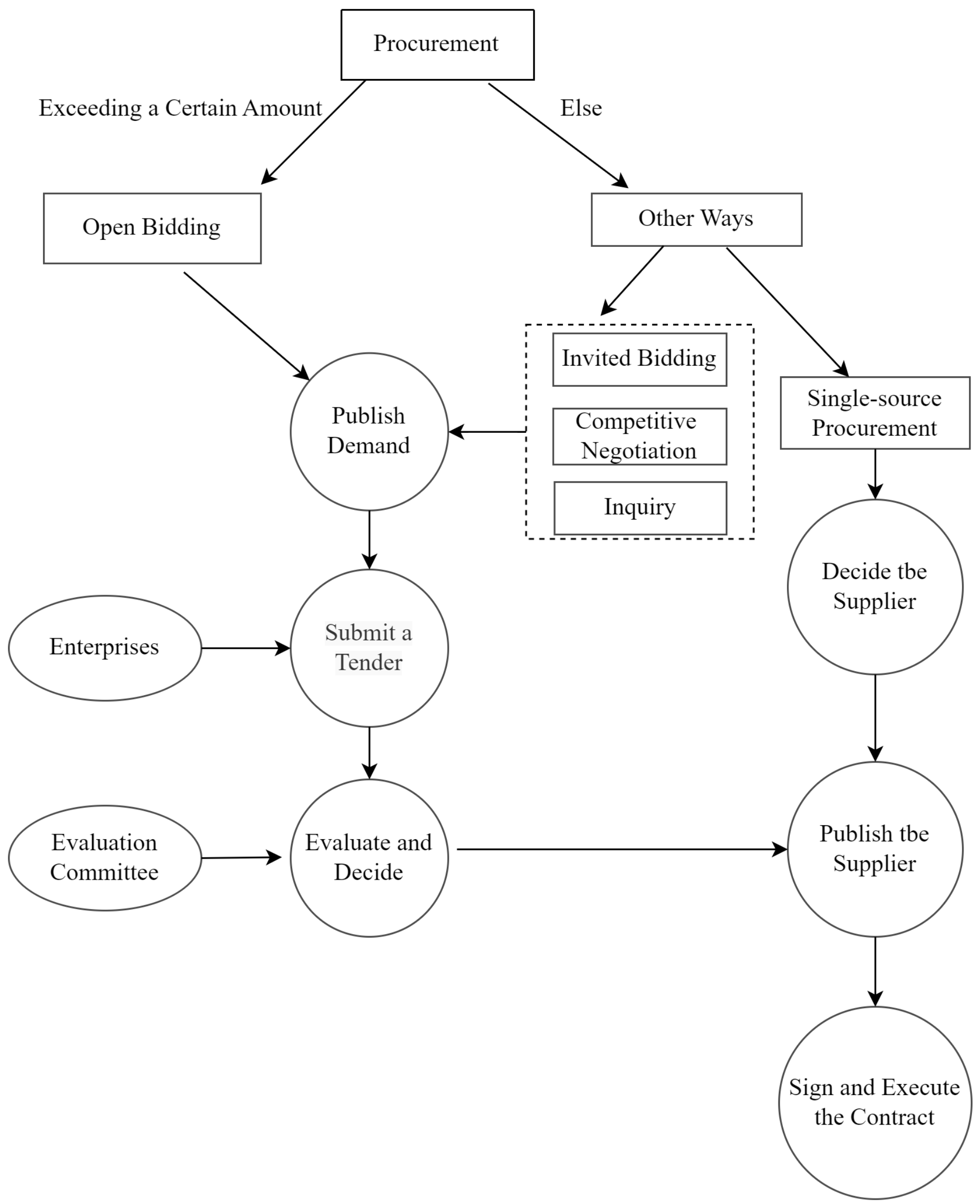
Source: China Procurement Yearbook, China Statistics Yearbook.

alternative procurement methods, including (1) invited bidding, (2) competitive negotiation, (3) inquiry, and (4) single-source procurement. Government agencies first publicly release a bidding announcement in open bidding, listing all requirements for goods, services, and projects. Then, potential vendors submit their tenders, and the bidding evaluation committee conducts an evaluation and determines the winner. The winning bidder is then announced on the official government procurement website. The announcement contains information on suppliers and the contract value. In procurement methods other than open bidding, the government can select suppliers following the procedure stipulated by the Government Procurement Law. Finally, government agencies disclose announcements containing contract information, regardless of the procurement method. Both central and local government procurement announcements are released on the official government website by the Ministry of Finance (`http://www.ccgp.gov.cn`), which serves as our key data source in the empirical analysis.

Despite various regulations on the procurement process, local officials have enormous discretion in assigning procurements; such discretion is a key premise of the hypothesis of political favoritism analyzed in this paper. As Lu and Wang (2022) note, local officials can directly influence the procurement process in three ways. The first is by manipulating the procurement method.

`https://www.zj.gov.cn/art/2017/11/10/art_1229620861_2396311.html`.

Figure 2: General Government Procurement Procedure



Court records on procurement-related corruption verdicts reveal that the government can designate suppliers by using noncompetitive bidding methods such as invited bidding or single-source procurement. The second way the local government designates winning bidders is by setting restrictive procurement requirements. Even in open bidding, the most competitive procurement method, officials can include specific requirements for bidders, such as firm size, sectoral affiliation, and performance, to guarantee that their preferred firm wins the bid. Finally, local officials can influence the bid evaluation committee, the members of which are usually a combination of government officials and experts from research institutions. On these committees, officials often interfere with the experts' professional evaluation by signaling their preferences over suppliers, steering the experts to provide higher scores to the preferred bidder.

The considerable discretion over procurers and high procurement contract values give rise to rampant corruption in the procurement process. Moreover, deep involvement of chief executives is an important feature of corruption in procurement bidding. According to a report by the CDIC, all 23 chief executives dismissed for corruption in Hainan province since the establishment of the province in 1988 were involved in procurement corruption.[8] With abundant corruption opportunities, procurement contracts have been one of the primary targets of the recent anticorruption effort. In 2015, the inspection team entered the National Government Offices Administration and the Departmental Affairs Management Bureaus of the CPC, two central agencies responsible for procurement. According to the postinspection report, roving inspectors interviewed 20 bureau leaders, imposed over 100 correction measures, and punished several officials.[9] Like their central peers, local leaders face tremendous career risks when participating in procurement corruption. For example, Zhang Shuyu, the former party secretary and director of the Meteorological Bureau, Gansu Province, was expelled from the CPC for "violating work discipline [... and] illegally interfering and meddling in government procurement projects." Zhang Guokai, former director of the Management Committee of the Dunhua Economic Development Zone, Jilin Province, was expelled from public office because for "making unqualified enterprises undertake projects through

[8] https://www.sohu.com/a/448574493_661255.

[9] http://politics.people.com.cn/n1/2016/0126/c1001-28084052.html

illegal operations." [10]

SOEs as a Safer Choice

Our theory suggests that the rent–survival trade-off manifests in a shift of benefits from private firms to SOEs. China serves as a quintessential case for examining this theory, as it has a mixed economy with a comparable size of the private and state sectors in its economy. In general, the state-sector economy accounted for approximately 40% of China's GDP and over 60% of its market capitalization in 2015 (Holz, 2018). The scale of SOEs continues to increase in China's economy. SOEs' total assets increased fourfold from 41.6 billion yuan in 2008 to 233.9 billion yuan in 2019. Meanwhile, China's GDP only doubled. Despite their growing size and the adoption of a series of efficiency-enhancing measures, SOEs still underperform non-SOEs. Using a sample of publicly traded firms, Jurzyk and Ruane (2021) finds that SOEs have lower productivity than non-SOEs in the same industry, with the productivity differences increasing between 2002 and 2009 and remaining sizable in 2019. Several reasons for SOEs' low efficiency include their policy burdens, such as promoting employment (Hsieh and Klenow, 2009) and maintaining social stability (Wen, 2020), and the poor management decisions (Estrin and Pérotin, 1991) and political inference (Tian and Estrin, 2008) to which they are often subject.

Although SOEs are generally less efficient than private firms in China, personnel and managerial relations with the state grant SOEs insider status vis-à-vis the regime. In China, SOEs are supervised by the State-Owned Assets Supervision and Administration Commission (SASAC), a government agency operating at various levels of government. The SASAC not only appoints top executives but also approves crucial corporate decisions such as mergers and acquisitions (Lin et al., 2020). Compared to private firms, SOEs enjoy various preferential treatments from the state, including easier entry permits, cheaper loans, and favorable legal judgments. The insider advantages have also manifested in the corruption crackdown, with SOEs enjoying greater immunity to

[10] https://www.ccdi.gov.cn/yaowen/202105/t20210502_241342.html

the crackdown than private firms, making them a safer choice for officials making procurement allocation decisions. While Chinese SOEs are notorious for their rampant corruption (Cheng, 2004), SOE managers are less likely to be punished than private entrepreneurs. A reason for this lighter punishment of SOE managers is that state procuratorates view SOE bribery schemes as beneficial for state assets. Court verdict data also empirically support the selective leniency toward SOEs. According to data from the Chinese Judgment Document Website, the official court adjudication information disclosure site, 1,591 private entrepreneurs have faced criminal punishment, accounting for 87.1% of corruption cases, while only 236 (12.9% of the cases) executives of state-owned enterprises have faced similar penalties (Zhang, 2017).

SOEs' greater immunity to corruption charges affects public officials' distributive decision-making. Faced with an increased risk of dismissal, government procurers are likely to sign more contracts with SOEs because such business relations do not catch the eye of anticorruption agencies. Our interviews provide suggestive evidence of this form of risk-driven favoritism. One interviewee in a central government agency mentioned that Xinhua bookstore, the largest state-owned bookstore in China, almost became the agency's only supplier of books after the start of the anti-corruption campaign because procuring books from a private bookstore could raise suspicions of corruption. Local officials behave similarly to reduce their career risks when making procurement decisions. Another interviewee, head of a local procurement office, told us, "Doing business with SOEs does not cause trouble. In contrast, doing business with private firms, even leading firms in a sector, will catch the eye of disciplinary and inspection commissions." Risk-driven favoritism is also reflected by the declining status of private firms in procurement. A private entrepreneur who does business in urban planning said in an interview that it has been significantly harder to obtain government contracts since the corruption campaign started in 2013 as procurement officials consider only SOEs because they are safer (*bao xian*) choices. Overall, these anecdotal cases reveal risk-driven favoritism toward SOEs. In the following sections, we provide systematic evidence on this theory using comprehensive data on government procurement in China.

Data

We systematically document risk-driven favoritism by collecting data from several sources. First, we gather data on public procurement contracts by scraping contract announcement texts from the website of Chinese Government Procurement (`ccgp.gov.cn`), the official procurement information disclosure agency. Figure A.2 shows an example of the raw contract text. After obtaining the texts of all procurement announcements, we use name entity detection algorithms to identify the key information on each contract, including the contract value, contract date, contract title, government agency, and procurement provider. In total, we gather approximately 2.9 million procurement contracts from 2008 through 2018.

In this study, we choose to match the information on procurement providers from the government procurement database with Chinese publicly traded firms for several reasons. First, using the listed firm sample allows more meaningful comparison of SOEs and non-SOEs because listed firms are similar in size. The whole sample contains a large number of small-value contracts, in which SOEs, which are usually large in firm size, do not participate in bidding. Second, the listed firm sample offers a better context for identifying risk-driven favoritism. The average contract value of listed firms (14.5 million yuan) is larger than that of the full sample (6.2 million yuan). In practice, the CDIC has no ability to monitor corruption in every contract but focuses on high-value contracts in auditing. Third, using the listed firm sample allows us to account for firm-level confounders such as firm size and performance that both affect procurement allocation and are highly correlated with firms' ownership type. These reasons aside, we acknowledge that the listed firm sample is not a representative sample of all firms that obtained procurement contracts, for which we lack comprehensive firm-level data.[11] Nevertheless, it reflects spatial variation similar to that of the full firm sample, as shown in Figure A.3, which is the main source of variation that we explore in the dyadic analysis. In practice, we identify whether a listed firm or its subsidiaries win a procurement bid by developing both exact and fuzzy firm name-matching methods (details of the method are in Appendix B). By applying the matching algorithms, we identify 171,024 con-

[11] The industrial and commerce registration database has only sparse information on all registered firms.

tracts (5.7% of all procurement contracts) obtained by 2,878 firms publicly traded on the two stock exchanges in China from 2008 to 2018.

Using the data on procurement contracts signed by listed firms, we examine the distributional outcome in government procurement by focusing on (1) the number of procurement contracts and (2) the gross value of procurement contracts obtained by each firm. Table A.1 shows firm-level summary statistics. Firms on average obtain approximately 3.5 procurement contracts with a gross value of 51 million yuan (7.5 million US dollars) per year.

In addition to the procurement information, we collect firm-level registration, performance, and ownership data from the China Stock Market & Accounting Research (CSMAR) database, a widely used vendor of firm data in China. Our key explanatory variable is firms' ownership structure. Following the literature, we define a firm as an SOE if its *controlling shareholder* is a state-owned enterprise or the SASAC. We also consider several firm-level confounders.[12] We first control for firm size because larger firms are more likely to be SOEs and have a better chance of making winning procurement bids. Following the literature, we use logged total assets as the proxy for firm size. In addition to firm size, firm performance is a possible confounder in that the government may deal with firms with better performance in procurement contracts. We use two measures of firm performance, logged revenue and returns on assets (ROA). We then obtain data on the ongoing anticorruption campaign in China, collecting the timeline of provincial-level roving inspections from the CCDI's official website. We collect information on subprovincial roving inspections from Wang (2022*a*).

[12]Central SOEs can also participate in local procurement bidding. For example, Datang Gaohong Data Network Technology Co., Ltd., a subsidiary of the well-known central SOE Datang Telecom Group, has obtained several contracts in network information projects.

Main Results

Effect of Political Risks on the SOE Premium

We empirically examine risk-driven favoritism using the firm–year panel dataset covering 2008 to 2018. Our baseline specification is a generalized difference-in-differences (DIDs) design that estimates the rise of the SOE premium, measured by the gap in contract volume and value between SOEs and non-SOEs, after the beginning of the campaign. Our main specification focuses on within-sector, across-firm variation in state ownership, allowing us to compare the procurement contracts received by SOEs with those received by non-SOEs in the same sector.[13] The model is specified as follows:

$$Y_{i(k)t} = \beta_0 + \beta_1 SOE_{i(k)t} * Campaign_t + \beta_2 SOE_{i(k)t} + \beta_3 X_{it-1} + \tau_{kt} + \delta_k + \gamma_t + \epsilon_{i(k)t},$$

where $Y_{i(k)t}$ denotes two outcome measures: (1) the number of procurement contracts (logged) and the total contract value obtained by firm i in year t. $SOE_{i(k)t}$ is a binary measure of the key explanatory variable, which is coded as 1 if firm i is an SOE in year t. $Campaign_t$ is a binary indicator for the campaign period. As the anticorruption campaign started in November 2012, we code $Campaign_t$ as 1 if the observation corresponds to years after 2012 and 0 otherwise. The key parameter of interest β_1 estimates the difference in the marginal effect of SOEs on the procurement contract number and value before and during the campaign. We control for a set of firm-level performance indicators, X_{it-1}, including ROA, firm size (measured by logged total assets), and logged revenue. All firm performance indicators are lagged to guarantee that covariate values correspond to the period prior to the realization of any impact on the outcome variable. [14] In addition to firm-level covariates, we include sector-specific time trends, τ_{kt}. Including the time trend ensures that

[13]We choose not to use within-firm estimation as our main specification because state ownership status shows little temporary within-firm variation in our sample. Over 71% of the firms are either SOEs or non-SOEs during all years studied in this paper. Nevertheless, the firm fixed effects specification shows a result consistent with our baseline results (Table A.3).

[14]Notably, observations for lagged variables in the year of IPO might be omitted because there are no values for the pre-IPO period.

Table 1: SOE Premium in Government Procurement (Firm-level Estimation)

	Procurement Number			Procurement Value		
	(1)	(2)	(3)	(4)	(5)	(6)
SOE*Campaign	0.230***	0.228***	0.192***	0.663***	0.666***	0.518***
	(0.045)	(0.046)	(0.046)	(0.143)	(0.147)	(0.147)
SOE	0.109***	0.001	0.023	0.422***	0.065	0.156
	(0.030)	(0.031)	(0.031)	(0.102)	(0.106)	(0.106)
Campaign	0.458***	0.279***	0.417*	1.561***	0.970***	1.638**
	(0.027)	(0.030)	(0.243)	(0.091)	(0.101)	(0.752)
Lagged ROA		-0.052	-0.032		-0.610	-0.537
		(0.146)	(0.147)		(0.437)	(0.439)
Lagged Size		0.110***	0.109***		0.404***	0.402***
		(0.025)	(0.025)		(0.075)	(0.075)
Lagged Revenue		0.066***	0.066***		0.175***	0.173***
		(0.020)	(0.020)		(0.061)	(0.061)
Observations	27,978	25,509	25,509	27,978	25,509	25,509
R-squared	0.091	0.140	0.145	0.081	0.127	0.133
Sector and Year FE	Y	Y	Y	Y	Y	Y
Sector Specific Time Trend	N	N	Y	N	N	Y

*Note: FE stands for fixed effects. The outcome variable in columns 1 – 3 is logged number of procurement contracts and that in columns 4 – 6 is logged gross procurement value. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1*

the effects of all unobserved sector-specific differences (e.g., sectoral trends in government procurement and the business and regulatory environment) that vary smoothly over time are removed from the estimation, β_1. δ_k and γ_t capture sector and year fixed effects, respectively. $\epsilon_{i(k)t}$ is the error term. We cluster standard errors at the firm level.

Table 1 shows the results. Column 1 includes the interaction term and SOE as well as sector and year fixed effects; the model yields statistically significant results for both SOE and the interaction term, SOE*Campaign. The estimation suggests that SOE premium increases by 23% since the start of the campaign, holding all else as equal. In columns 2 and 3, we gradually include firm covariates and sector-specific time trends, and the estimate of the interaction terms declines slightly but is still statistically significant at the 1% level. In columns 4 to 6, we examine the effect of SOE on procurement value using the same specifications as in columns 1 to 3. Consistent with the findings on contract volume, the models yield positive and significant estimates for the

SOE*Campaign interaction, suggesting a rising SOE premium in the contract value in the wake of the campaign. Our estimates of the SOE premium are statistically significant and economically meaningful. The most conservative estimation shows that the SOE procurement premium increased by approximately 19% for the contract volume and 52% for the procurement value after the campaign started in 2013. Given that the mean value of procurement received by listed firms is approximately 52 million yuan (7.6 million US dollars), the state ownership premium is approximately 27.04 million yuan (3.98 million US dollars), equivalent to 26% of the median gross profits (103 million RMB) earned by these firms. Overall, the estimated gross size of SOE premium during the campaign (2012–2018) is approximately 194.4 billion yuan (28.6 billion US dollars).[15] How large is this SOE premium? For context, we can take the country's GDP as a reference. The estimated size of SOE premium is roughly close to the GDP of Nepal (30.6 billion USD) in 2018.

Beyond showing the a sizable, risk-driven SOE premium, we are interested in the risk effect on procurement through the different procurement methods. As earlier literature suggests, political favoritism is more salient in noncompetitive procurement contracts (Dahlström, Fazekas and Lewis, 2021). We examine how risk-driven favoritism affects procurement with different levels of competitiveness by dividing contracts into two types—those conferred through open bidding ($\geq 70\%$ of all contracts) and others—and estimate the campaign's effect on each group using the baseline specification. Table A.2 shows the results. Consistent with our baseline results, the SOE premium increases in terms of the volume and value of both open bidding contracts and others. Interestingly, the estimated premium increase is slightly larger in procurement through nonopen bidding, where officials can have more discretion than under the more competitive method (open bidding).

To verify the validity of our estimation on the SOE premium, we need to consider the parallel trends assumption, a crucial premise of the DID design. If the parallel trends assumption holds, we should observe no divergence between SOEs and non-SOEs in their trends of procurement value and number before the start of the campaign. We are also interested in the lasting effect of the

[15] 52 million * 0.52 * 1199 SOEs * 6 years.

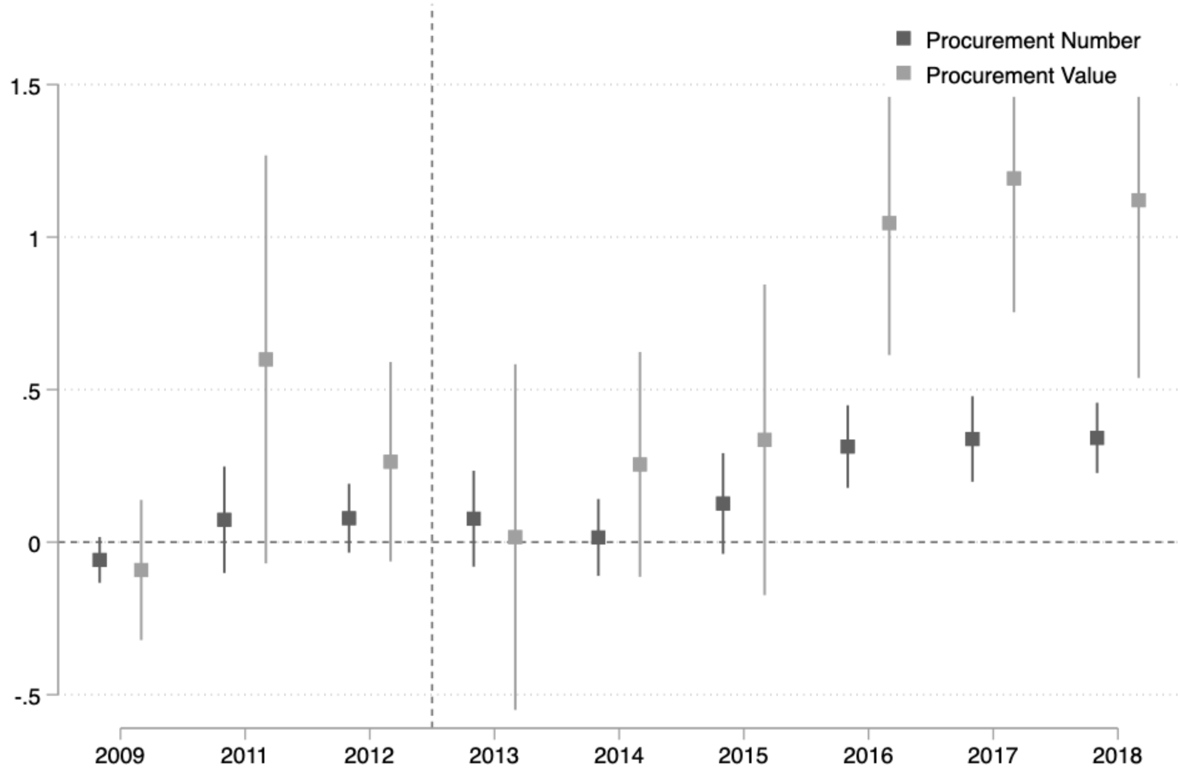
anticorruption campaign, specifically, the year when the SOE premium began to be salient. We empirically examine the parallel trends assumption and the lasting effect by employing a dynamic effect analysis with the following model:

$$Y_{i(k)t} = \beta_0 + \sum_{\tau=2009}^{2018} \beta_\tau SOE_{i(k)t} * \tau_t + \beta_2 SOE_{i(k)t} + \beta_3 X_{it-1} + \tau_{kt} + \delta_k + \gamma_t + \epsilon_{i(k)t},$$

where we replace the baseline interaction term, $SOE * Campaign$, with a set of dummies that indicate the interaction between each year (τ_t) and state ownership status ($SOE_{i(k)t}$). We choose the beginning year, 2008, as the reference group. β_τ is the set of parameters of interest that documents the dynamic effect. Figure 3 shows the visualized estimates for $\beta_{2009}, \beta_{2010}...\beta_{2017}, \beta_{2018}$ on the procurement number and value. We find strong support for the parallel trends assumption in that the increase in the estimated SOE premium in the precampaign period (2009–2012) is close to zero. Interestingly, the dynamic analysis shows that the SOE premium in contract value has increased since the second year of the campaign (2014) and grew in the later years of the campaign (2016–2018).

In addition to examining the dynamic effects, we conduct several additional robustness checks. While our baseline specification is a within-sector estimation, we alternatively use the firm fixed effects model to estimate the marginal difference in the effect of state ownership on the procurement number and value before and during the campaign. Table A.3 presents the result, which is consistent with our main result. Second, we use an alternative measure of SOE status by focusing on the actual controller. In some cases, state-affiliated agencies can control a firm's operation through investment relationships and agreements without holding a major shareholder status. Considering the actual controller information provided by CSMAR, we show that our main finding holds under this alternative measure of SOE status in Table A.4. Finally, we conduct a subsample analysis that estimates the effect of state ownership on government procurement for subsamples of observations from the years before (2008–2012) and during (2013–2018) the campaign (Table A.5). While

Figure 3: Dynamic Effect Analysis



Note: The black dots and lines denote the point estimates and the 95% confidence intervals for the effect of $SOE_{i(k)t} * Year_{2009}, SOE_{i(k)t} * Year_{2010} ... SOE_{i(k)t} * Year_{2017}, SOE_{i(k)t} * Year_{2018}$ *on the procurement number, and the gray points and lines denote those for the effect on the procurement value.*

SOEs have more winning procurement bids and more valuable contracts than non-SOEs in both periods, the point estimate for the campaign period is larger than that for the precampaign period, underscoring the validity of our baseline findings. Overall, none of these robustness tests challenge our main findings.

Effect of Survival Concerns

While the firm-level analysis yields sizable estimates for the state ownership premium, we further demonstrate that this premium is driven by local officials' survival concerns. To do so, we focus on the roving inspections conducted by the CCDI. Between 2013 and 2018, the CCDI conducted 14 rounds of inspections of 31 provincial units. While no evidence suggests that the party center randomly assigns inspection teams to provinces, CCDI inspections are exogenous to local procurement allocation decision-making for three reasons. First, local officials do not know whether their jurisdiction will be inspected beforehand. Second, local officials are not informed about the scope of the inspection, as the number of provincial units in each round of inspection varies from four to ten. Third, previous inspection experience does not lead to future immunity to inspection, as the CCDI clearly states that each provincial unit can be inspected multiple times. Considering these aspects together, we leverage this exogenous provincial-level variation in uncertainty over corruption dismissals to examine provincial leaders' procurement allocation decision-making. Specifically, we expand the data to the province-by-firm level. In line with our baseline specification, we focus on the within-sector variation in state ownership by conducting a dyadic regression specified as follows:

$$Y_{ip(k)t} = \beta_0 + \beta_1 SOE_{it} * Inspection_{pt} + \delta_{pk} + \gamma_{pt} + \tau_{it} + \epsilon_{ipt},$$

where $Y_{ip(k)t}$ denotes the two outcome variables: the number of procurement contracts (logged) and the total value of contracts obtained by firm i from province p in year t.[16] SOE_{it} is a dichotomous measure of firm ownership. We code it as 1 if firm i in year t is owned by the state and 0 otherwise. $Inspection_{pt}$ is a binary indicator coded as 1 if the CDIC conducted a roving inspection in province p in year t and 0 otherwise. We interact SOE with $Inspection$ to obtain β_1 to estimate the increase in the SOE premium in government procurement in response to roving inspections. Taking advantage of the dyadic data structure, we exclude the effect of unobservables using high-dimensional fixed effects: specifically, sector-by-year fixed effects (τ_{it}) to eliminate impacts from sector–year-specific shocks (e.g., global energy crises, foreign sanctions); province-by-year fixed effects (γ_{pt}) to account for province–year confounders (e.g., provincial leader's characteristics, social-economic conditions of provinces, provincial-level political turnover); and province-by-sector (δ_{pk}) fixed effects to account for confounders such as sector-specific concentrations in certain provinces (e.g., the manufacturing sector in Guangdong and the coal mining industry in Shanxi). We cluster the

[16]Figure A.3 shows considerable provincial-level variation in the procurement volume.

standard errors at the firm level.

Table 2: Dydadic Analysis

	Procurement Number				
	08-18				13-18
	(1)	(2)	(3)	(4)	(5)
SOE	0.015***	0.015***	0.015***		
	(0.003)	(0.003)	(0.003)		
Inspection	0.002***				
	(0.001)				
SOE*Inspection	0.013***	0.013***	0.013***	0.005***	0.005**
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Sector-by-year FE	Y	Y	Y	N	N
Province-by-Year FE	N	Y	Y	Y	Y
Province-by-Sector FE	N	N	Y	N	N
Firm-by-Year FE	N	N	N	Y	Y
Province-by-Firm FE	N	N	N	Y	Y
N	869,209	869,209	869,209	869,209	553,722
Adjusted R^2	0.015	0.037	0.045	0.509	0.585
	Procurement Value				
	08-18				13-18
	(1)	(2)	(3)	(4)	(5)
SOE	0.069***	0.068***	0.068***		
	(0.013)	(0.013)	(0.013)		
Inspection	0.010***				
	(0.004)				
SOE*Inspection	0.057***	0.057***	0.057***	0.022**	0.021**
	(0.016)	(0.016)	(0.016)	(0.010)	(0.010)
Sector-by-year FE	Y	Y	Y	N	N
Province-by-Year FE	N	Y	Y	Y	Y
Province-by-Sector FE	N	N	Y	N	N
Firm-by-Year FE	N	N	N	Y	Y
Province-by-Firm FE	N	N	N	Y	Y
N	869,209	869,209	869,209	869,209	553,722
Adjusted R^2	0.014	0.031	0.037	0.365	0.414

*Note: FE stands for fixed effects. The upper panel shows the result on procurement number (logged) and the lower panel shows that on procurement value (logged). In each panel, the time frame in columns 1 – 4 is 2008–2018 and that in coulumn 5 is 2013–018. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1*

Table 2 shows the results on procurement volume (upper panel) and procurement value (lower panel). In each panel, we gradually include sector-by-year, province-by-year, and province-by-sector fixed effects from Columns 1 to 3. The full model (column 3) yields a positive and statistically significant coefficient for the interaction term $SOE * Inspection$, suggesting that political shocks driven by roving inspections have a strong allocative effect on government procurement. Beyond the within-sector estimation, we are concerned about confounders at the firm-by-year level (e.g., firm performance) and province-by-firm level (e.g., firm political connections in certain provinces). Column 4 presents the estimation using firm-by-year, province-by-firm, and province-by-year fixed effects. While the coefficient on the interaction decreases, it is still positive and significant at the 1% level. In column 5, we limit the sample to the campaign period (2013–2018). The estimation yields results consistent with those using the full panel (2008–2018). The lower panel uses the same model specifications as in the upper panel. Again, the estimation yields positive and significant estimates for the interaction term. Overall, the dyadic analysis suggests that provincial governments allocate disproportionately more procurement contracts in response to roving inspections conducted by the center.

In addition to the above specification, we conduct several sets of analyses to demonstrate robustness. We first conduct a placebo test by estimating the interaction of SOE and a set of fake inspection periods ($Inspection_t + n, n = -3, -2, -1, 1, 2, 3$). We show null results for these fake-treatment interactions, confirming the exogeneity of the roving inspections (Figure A.4). Second, we check that the result holds under an alternative measure of state ownership: actual controller status (Table A.6). Third, we check robustness when subprovincial roving inspections are taken as political shocks to examine the survival concern mechanism. Following the same approach in the province-level analysis, we first construct prefecture-by-firm dyadic data covering 2008 to 2017 using subprovincial-level inspection data from Wang (2022*a*).[17] We interact the dummy for prefectural-level roving inspections with the state ownership dummy. Table A.7 shows a pattern consistent with that in our province-by-firm dyadic analysis: the SOE premium in procurement vol-

[17] Wang (2022*a*) records prefectural roving inspections occurring between 2013 and 2017.

ume and value provided by the prefectural government increases drastically when the prefecture is under inspection. Finally, we change the level of clustering of the standard errors in the dyadic analysis. We cluster the standard errors at the dyad level (province–firm). The estimates under this alternative clustering are presented in Table A.8 and remain statistically significant, providing additional support for our main finding.

Alternative Explanations

In addition to the survival concern mechanism, several alternative explanations can account for the rise in the SOE premium after 2013. First, the anticorruption campaign may have a chilling effect not only on public officials. A corporate governance explanation is that the anticorruption effort, including enhanced auditing and dismissal of corrupt managers, improved corporate governance, making SOEs more competitive in procurement bidding. To rule out this confounding effect of the campaign, we examine how the SOE premium in firm performance increased after the start of the campaign. We employ the same specification as our baseline, replacing procurement contracts with two performance indicators, ROA and return on equity (ROE). Table A.9 shows the results. We find that the SOE premium did not significantly change after the launch of the campaign, as shown by the extremely small and statistically insignificant estimates of the interaction term.

Another competing explanation is the local policy focus. It is likely that the SOE premium is driven by the policy agenda favoring SOEs rather than the corruption crackdown per se. In addition to the within-campaign analysis on roving inspections, we address this concern by developing a proxy for the policy focus on SOEs. Following the literature (Jiang, 2018), we use annual work reports to gauge provincial governments' policy focus on SOEs. To do so, we first manually collect the provincial government work reports and compute the mention frequency of SOE (*guo you qi ye*) and its abbreviation (*guo qi*). We then match firms' headquarters location with this provincial-level policy focus measure. A higher value of SOE frequency indicates a stronger focus on the role of SOEs in certain localities.[18] We include this policy focus measure as an additional control

[18]Figure A.5 shows that the time trend of our measure of SOE-focused policy decreases for years after 2008 but

in our baseline specification. Table A.10 shows that after we control for this factor, the coefficient on our key variable of interest, the SOE*Campaign interaction, remains stable and significant, underscoring that our main result is not driven by local policy preference.

Policy focus aside, local governments may favor SOEs for a fiscal reason. In the past decade (2013–2022), Chinese local governments have faced an increased fiscal burden as the growth rate of public revenue has gradually declined while that of public spending has remained high. Consequently, rising debt has become a severe issue faced by local political leaders. Local governments allocate SOEs more procurement orders because SOEs have better financial conditions that allow the government to owe the firms money and pay them later. In other words, SOEs serve as money bags whereby local governments smooth their debt obligations. To rule out this alternative explanation, we analyze firm receivables, which refer to debts owed by customers for goods or services that have been delivered but not yet paid for. If local governments offer procurement contracts to SOEs to balance debt, we would expect a stronger correlation between procurement contracts and receivables among SOEs than among non-SOEs after 2013. Table A.11 shows the result. The null effect of the interaction term suggests that the elasticity of the procurement order or value to the absolute (logged receivables) and relative (ratio of receivables to business income) measures of receivables is not significantly different between SOEs and non-SOEs. This evidence runs counter to a financial pressure mechanism.

Finally, the international environment may also affect domestic distributive politics. We address this concern by ruling out the possibility that the SOE premium is driven by the Sino–US trade war, with the Chinese government providing assistance to SOEs to help them overcome geopolitical challenges in global trade. We consider this concern by truncating the sample to the pre–trade war period and excluding sectors affected by the trade war. Table A.12 shows the result, which exhibits a consistent pattern that demonstrates the SOE premium increase after the start of the campaign. Overall, we show that political favoritism toward SOEs is not driven by enhanced SOE performance, macro policy shifts, concerns over government debt, or geopolitical challenges.

bounces back sharply for years after 2013, suggesting a possible major policy change after Xi Jinping assumed office.

Efficiency Losses from (Mis)Allocation

A remaining task is to examine the size of the distortions from this risk-driven favoritism. We address the efficiency question by focusing on the productivity consequences of political favoritism. Indeed, the efficiency implications of the rising SOE premium are unclear a priori. If SOEs are less efficient than non-SOEs because of poor management and political interference, growing favors toward SOEs can reduce resource allocation efficiency. In contrast, the favorable distribution toward SOEs may remedy the allocation bias from the precampaign period, when unqualified non-SOEs commonly bribed officials to obtain more contracts. In this case, the corruption crackdown may have crowded out unqualified non-SOEs, thereby enhancing allocation efficiency. We thus address this empirical question by conducting two sets of analyses. We first conduct an ex ante analysis of the selection of winning bidders. We show that the quality of winning bidders, measured by firm productivity, declined after the campaign began in 2013. We also conduct an ex post evaluation, estimating the extent to which winning procurement contracts affects firm productivity. Consistent with the efficiency losses argument, we show that additional contracts obtained by SOEs indeed decrease firm productivity.

Ex Ante Analysis

Our ex ante analysis focuses on the quality of winning bidders. We measure bidder quality using total factor productivity (TFP), following common practice in economics (Bils, Klenow and Ruane, 2021). TFP gauges a firm's productivity by computing its output given a certain amount of inputs. In this study, we follow the method developed by Jurzyk and Ruane (2021), computing our TFP measure as value added divided by the geometric average of capital (measured as fixed assets) and labor (measured as employment), corresponding to a standard Cobb–Douglas production function. A higher TFP value means that a firm can generate more revenue given a fixed amount of inputs.[19] Details of the TFP computation are shown in Appendix C.

[19]TFP here is a measure of revenue productivity (TFPR), which is different from firm technical efficiency (often referred to as physical productivity $A_{i(s)}$ or TFPQ).

We use firm–year panel data on all winning procurement bidder firms to estimate the extent to which the campaign affected winners (a detailed description is shown in Appendix D). We regress firm productivity on the campaign dummy, including year trends, sector fixed effects, and sector-specific time trends. The upper panel of Table D.1 shows the results. Column 1 includes only the sector fixed effects and overall time trend. Column 2 includes sectoral fixed effects and sector-specific time trends. Column 3 adds the control variables, and column 4 adds the mention frequency of SOEs in the provincial government work report. The results show that the average productivity of government procurement winners fell by 12% to 15.4% after the start of the anticorruption campaign. To address the concern that officials may determine government procurement allocations considering a firm's productivity information for the previous year, we use the productivity of firm i in year $t-1$ as the outcome variable to check robustness. The results in the lower panel of Table D.1 show a decline in the quality of winning procurement bidders.

Ex Post Analysis

Beyond the declining quality of winning procurement bidders, we conduct an ex post analysis to estimate the extent to which procurement deals received by different firms affect firm productivity. To do so, we first conduct an eyeball test of allocative efficiency before and during the anticorruption campaign. Here, we present SOEs' and non-SOEs' residual productivity, conditioning on sector and year fixed effects; this metric allows us to compare the productivity of firms in the same sector and year. In support of the distorting nature of political favoritism, we show two stylized facts. First, SOEs were less productive than non-SOEs before the campaign—a crucial premise of the argument that allocation distortions arise from officials contracting more with inefficient firms. The left panel of Figure 4 shows a salient difference between SOEs and non-SOEs: the former were much less productive than the latter in the precampaign time. Second, the right panel of 4 suggests that the productivity gap between SOEs and non-SOEs widened during the campaign. Compared to its precampaign level shown in the left panel, SOEs' productivity declined sharply, while non-SOEs experienced a relatively small drop in their firm productivity, suggesting an exacerbation of

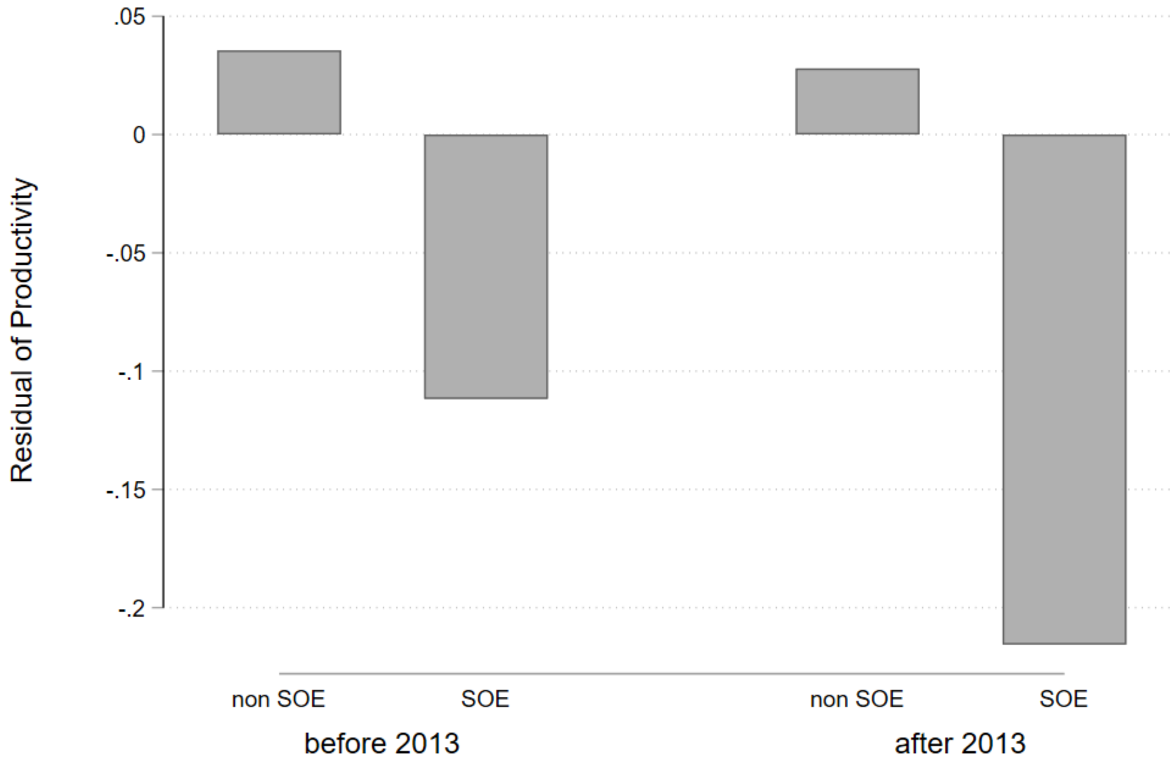


Figure 4: Productivity Difference Between SOEs and Non-SOEs
Note: The bar denotes the residual value of productivity conditional on inclusion of two-way (industry–year) fixed effects and industry-specific linear year trends. The graph reflects productivity differences between SOEs and non-SOEs in the same industry and year.

inefficiency.

While the eyeball test provides suggestive evidence on the widened productivity gap, we further estimate it parametrically using a two-stage least squares (2SLS) specification. (The detailed description is shown in Appendix D). Table D.2 shows that firm productivity decreases by 0.32% and 0.09% with a 1% increase in procurement volume and a 1% increase in procurement value. As our baseline model shows that procurement contracts obtained by SOEs sharply increased after 2013, the 2SLS model suggests that the campaign has deteriorated distribution efficiency, resulting in a further decline in the productivity of the state sector. Our reduced-form estimation shows a pattern consistent with that of the 2SLS results: the productivity gap between SOEs and non-SOEs further increased by approximately 9% after the start of the campaign.

To summarize, our ex ante and ex post analyses demonstrate the distortionary impact of risk-driven favoritism. First, political risks deteriorate the selection of winning procurement bidders. Moreover, despite obtaining a windfall of government procurement contracts, SOEs have not caught up to non-SOEs in productivity. Instead, the productivity gap has widened, suggesting the distortionary nature of political favoritism.

Conclusion

By showing a sizable risk-driven favoritism and its distortion in public procurement allocation, this study advance the understanding of anticorruption reform. Theoretically, the key argument of this paper is in line with a growing political science scholarship that documents behavioral changes among public officials in environments with high political uncertainty (Wang, 2022*a*; Li, Li and Zhang, 2023). We show that officials subject to survival concerns make economic decisions that tremendously distort resource allocation. Empirically, this study is also related to research on the economic effects of the anticorruption campaign. The existing economics literature documents the campaign as a disruptive shock affecting firm performance, investment, and innovation (e.g., Kong, Wang and Wang, 2017; Xu and Yano, 2017). This study focuses on the effect of the corruption crackdown on public resource allocation and the associated efficiency losses.

Broadly, our study contributes to scholarship on rising state capitalism in emerging economies (Naughton and Tsai, 2015; Pearson, Rithmire and Tsai, 2021). Established scholars of the developmental state contend that state capitalism emerges when governments strategically allocate more resources to government-controlled enterprises using industrial policies (Johnson, 1982; Leftwich, 1995). In contrast to works emphasizing this industrial policy mechanism, our paper is more related to a burgeoning body of literature on how states control the economy using the ownership mechanism (Leutert and Eaton, 2021; Leutert, 2018). In particular, we propose a political survival mechanism to account for the resurgence of SOEs in China and show that the rising SOE premium has come at the expense of economic efficiency and public welfare.

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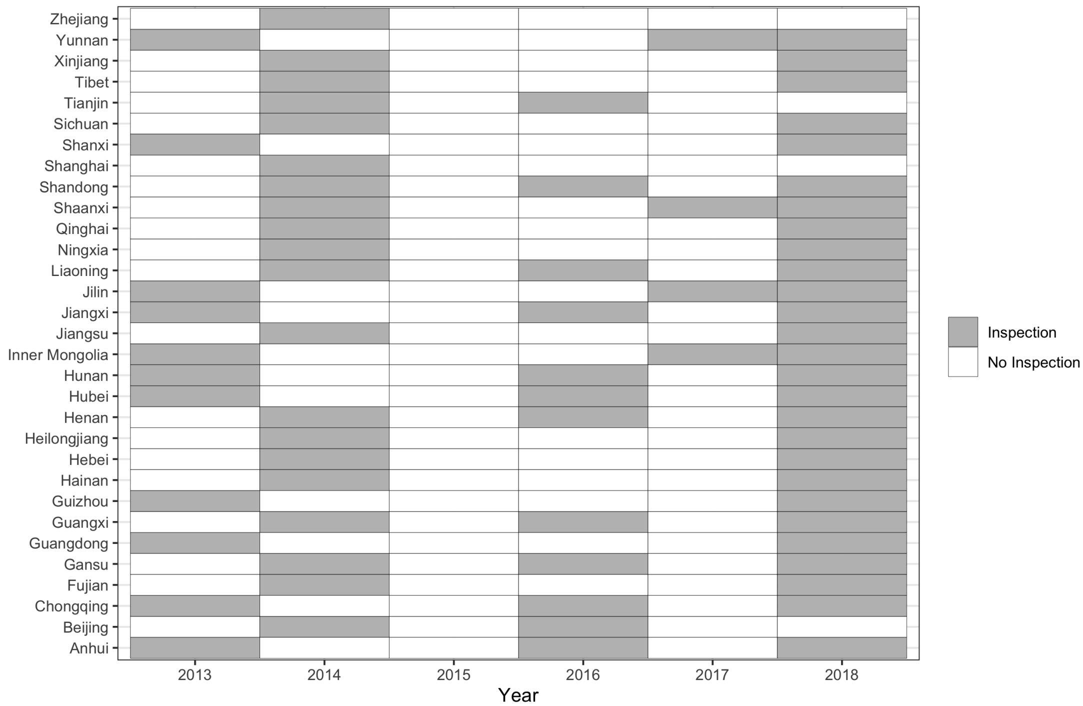
Supplementary Information

A Tables and Figures

Figure A.1: Provincial-level Roving Inspection



Note: The gray grid denotes the provincial unit that experiences the roving inspection by the CCDI in a certain year. The white grid denotes no inspection is conducted in that provincial unit in a certain year.

Figure A.2: Example of Procurement Raw Data

财政部唯一指定政府采购信息网络发布媒体 国家级政府采购专业网站　　服务热线：400-810-1996

政策法规　标讯频道　中央采购　地方采购　案例解读　购买服务　PPP频道　GPA专栏　采购百科　热点专题

中国政府采购网　首页 » 地方标讯 » 中标公告

北京市海淀区新闻中心新闻演播室改造项目

2014年12月05日 18:45 来源：中国政府采购网 【打印】

项目名称：北京市海淀区新闻中心新闻演播室改造项目 -> Procurement Name
招标编号：0773-1441GNOA01423 -> Procurement Code
采购单位：北京市海淀区新闻中心 -> Buyer Agency
采购单位地址：北京市海淀区西四环北路11号 -> Buyer Address
采购单位联系人：曹爱东
采购单位联系方式：010-88487259

采购方式：公开招标 -> Procurement Means
评分方法和标准：综合打分法
招标公告日期：2014年11月14日 -> Announcement Date
评标日期： 2014年12月05日
评标委员会成员：郭赤兵、王宇、徐冬丽、翟阳、曹爱东

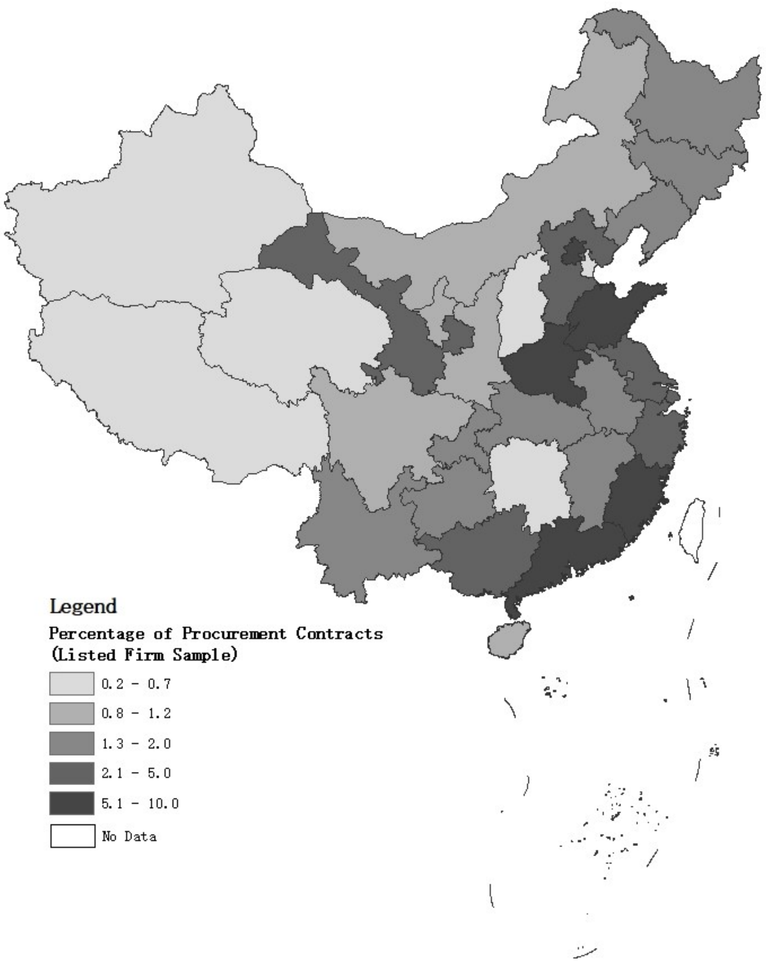
中标商名称：**北京昱林科鸿科技发展有限公司** -> Final Bidder
中标金额：人民币贰佰陆拾叁万玖仟元整（¥2,639,000.00）-> Contract Value
中标商地址：北京市朝阳区安翔北里11号创业大厦C座207室 -> Bidder Address

采购代理机构全称：中金招标有限责任公司
采购代理机构地址：北京市海淀区西三环北路21号久凌大厦15层
采购代理机构联系人：赵强
采购代理机构联系方式： 010-68405023
传真： 010-68405006

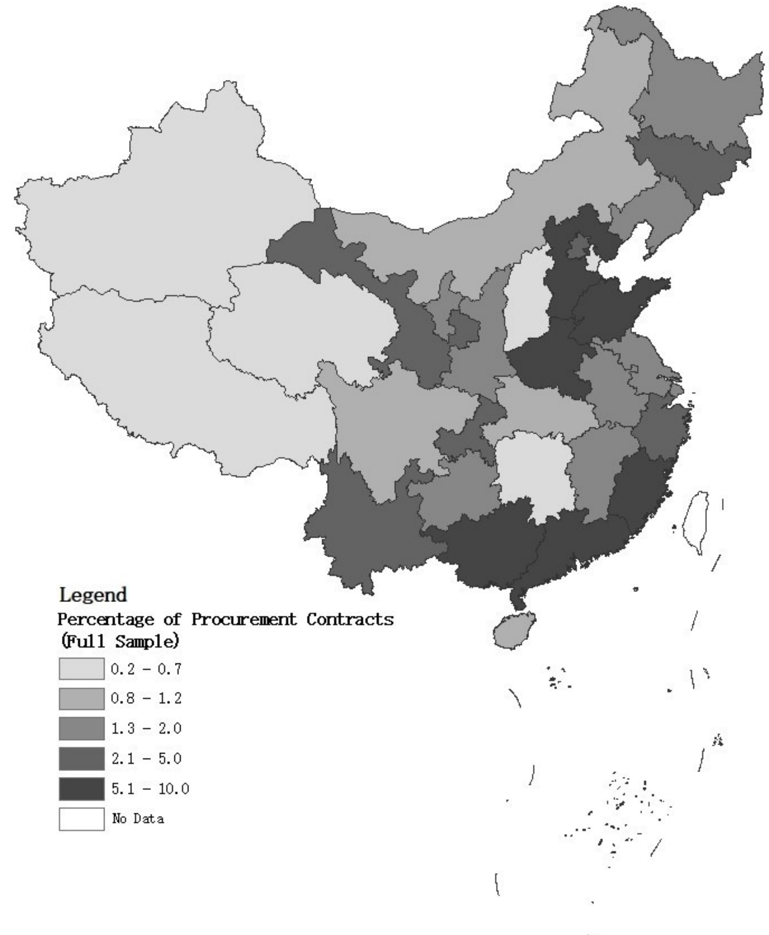
中金招标有限责任公司

2014年12月05日

Figure A.3: Percentage of Government Procurement Contracts by Province



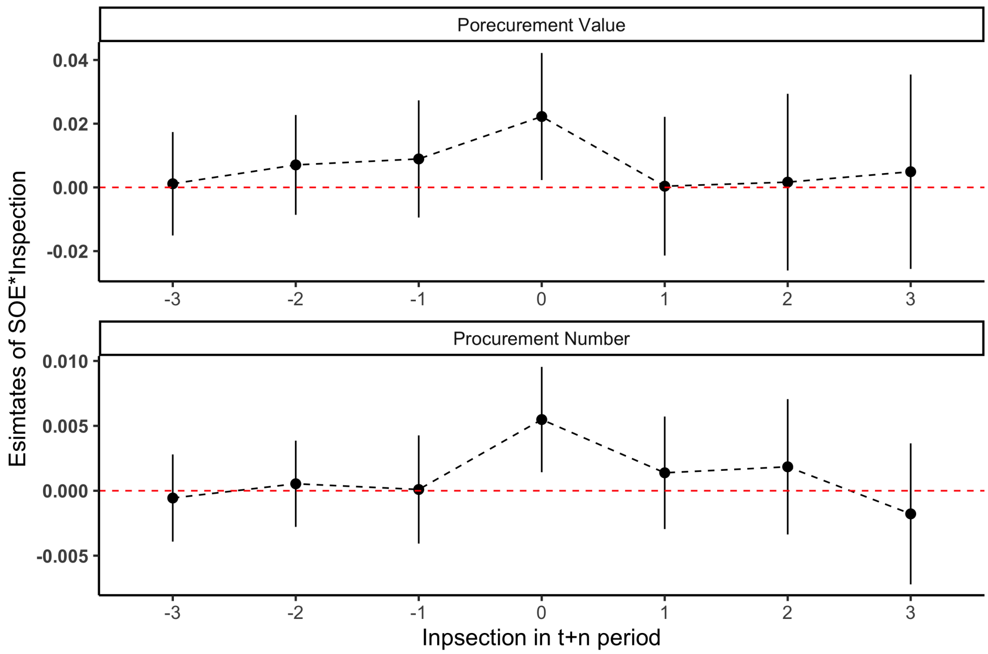
A.1 Listed Firms Sample



A.2 Full Sample

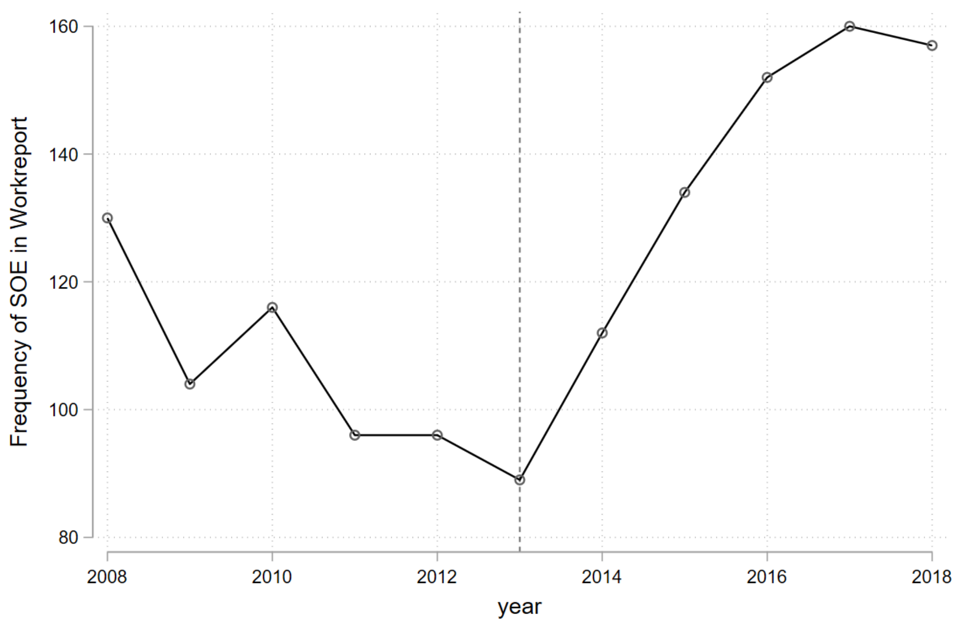
Note: The map visualizes the procurement contract percentage of number for each province units. The darker color means higher gross procurement percentage.

Figure A.4: Placebo Tests Using Fake Inspection Periods



Note: The point and lines denote point estimate and confidence intervals for $SOE_{it} * Inpection_{t+n}$ if $n = -3, -2, -1, 0, 1, 0, 2, 3$, respectively. The estimation uses the specification of Column 3, Table 2. The upper panel shows the results on logged procurement contract value and the lower panel shows that on the logged number of procurement contracts.

Figure A.5: Frequency of “SOE” in Work Report of Provincial Government



Note: Authors manually collect the full text of work report of provincial governments. The frequency of ”SOE” include both the ”state-owned enterprises”(国有企业) and its abbreviation (国企).

Table A.1: Firm-level Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Procurement Number	29,462	3.521	14.886	0	507
Procurement Value (million yuan)	29,462	51.521	719.283	0	49,374
SOE	28,039	0.173	0.378	0	1
Campaign	29,462	0.639	0.480	0	1
ROA	29,050	0.047	0.074	−0.353	0.258
Revenue (million yuan)	28,516	8,809.621	66,200.990	0.000	2,891,179.000
Size	29,050	22.034	1.428	19.022	26.593

Table A.2: Analysis of Sub-types of Procurement

	Procurement Number		Procurement Value	
	Open	Other	Open	Other
	(1)	(2)	(3)	(4)
SOE*Campaign	0.486***	0.492***	0.141***	0.164***
	(0.129)	(0.131)	(0.036)	(0.039)
SOE	0.008	0.163*	-0.007	0.018
	(0.079)	(0.092)	(0.021)	(0.025)
Campaign	1.211*	0.787	0.286	0.188
	(0.647)	(0.637)	(0.193)	(0.184)
Lagged ROA	-0.180	-0.414	0.042	-0.049
	(0.368)	(0.366)	(0.108)	(0.118)
Lagged Size	0.292***	0.354***	0.073***	0.092***
	(0.064)	(0.065)	(0.019)	(0.021)
Lagged Revenue	0.121**	0.124**	0.044***	0.045***
	(0.050)	(0.051)	(0.014)	(0.016)
Observations	25,509	25,509	25,509	25,509
R-squared	0.103	0.126	0.114	0.137
Sector and Year FE	Y	Y	Y	Y
Sector Specific Time Trend	Y	Y	Y	Y

*Note: FE stands for fixed effects. The outcome variable in columns 1 – 2 is logged number of procurement contracts and that in columns 3 – 4 is logged gross procurement value. Columns 1 and 3 are open bidding procurement and columns 2 and 4 are other forms of procurement, including invited bidding, competitive negotiation, inquiry, and single-source procurement *** p<0.01, ** p<0.05, * p<0.1*

Table A.3: Firm FE model

	(1)	(2)	(3)	(4)	(5)	(6)
	Procurement Number			Procurement Value		
SOE*Campaign	0.124***	0.116***	0.115***	0.362***	0.348***	0.351***
	(0.034)	(0.035)	(0.034)	(0.117)	(0.121)	(0.121)
SOE	-0.085***	-0.082***	-0.085***	-0.293***	-0.272***	-0.282***
	(0.024)	(0.024)	(0.024)	(0.085)	(0.086)	(0.086)
Campaign	0.609***	0.519***	0.515***	2.018***	1.749***	1.716***
	(0.026)	(0.033)	(0.033)	(0.093)	(0.118)	(0.118)
Lagged ROA		0.082	0.068		0.229	0.191
		(0.075)	(0.076)		(0.291)	(0.292)
Lagged Size		0.041**	0.041**		0.113*	0.117*
		(0.019)	(0.018)		(0.066)	(0.064)
Lagged Revenue		0.023	0.019		0.089*	0.079
		(0.015)	(0.014)		(0.054)	(0.053)
Observations	28,039	25,548	25,509	28,039	25,548	25,509
R-squared	0.766	0.770	0.771	0.636	0.644	0.646
Firm and Year FE	Y	Y	Y	Y	Y	Y
Sector Specific Time Trend	N	N	Y	N	N	Y

*Note: FE stands for fixed effects. The outcome variable in columns 1 – 3 is logged number of procurement contracts and that in columns 4 – 6 is logged gross procurement value. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1*

Table A.4: Alternative Measure of SOEs

	(1)	(2)	(3)	(4)	(5)	(6)
	Procurement Number			Procurement Value		
SOE (actual controller)*Campaign	0.266***	0.261***	0.233***	0.849***	0.826***	0.693***
	(0.027)	(0.029)	(0.029)	(0.089)	(0.094)	(0.095)
SOE	0.190***	0.037	0.051	0.664***	0.175	0.244**
	(0.032)	(0.035)	(0.034)	(0.102)	(0.112)	(0.111)
Campaign	0.396***	0.239***	0.298	1.339***	0.832***	1.252*
	(0.024)	(0.029)	(0.232)	(0.083)	(0.098)	(0.729)
Lagged ROA		0.100	0.111		-0.082	-0.043
		(0.148)	(0.149)		(0.442)	(0.444)
Lagged Size		0.101***	0.100***		0.374***	0.373***
		(0.025)	(0.025)		(0.075)	(0.075)
Lagged Revenue		0.056***	0.056***		0.138**	0.138**
		(0.020)	(0.020)		(0.060)	(0.060)
Observations	27,980	25,509	25,509	27,980	25,509	25,509
R-squared	0.112	0.148	0.152	0.103	0.135	0.139
Sector and Year FE	Y	Y	Y	Y	Y	Y
Sector Specific Time Trend	N	N	Y	N	N	Y

*Note: FE stands for fixed effects. The outcome variable in columns 1 – 3 is logged number of procurement contracts and that in columns 4 – 6 is logged gross procurement value. Standard errors are clustered at the firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Table A.5: Before and During Campaign Subsample Analysis

	(1)	(2)	(3)	(4)
	2008-2012		2013-2018	
	Number	Value	Number	Value
SOE	0.063**	0.273**	0.192***	0.423***
	(0.031)	(0.107)	(0.048)	(0.105)
Lagged ROA	-0.132	-0.422	0.090	-0.549
	(0.151)	(0.484)	(0.192)	(0.440)
Lagged Size	0.020	0.115	0.149***	0.404***
	(0.028)	(0.091)	(0.028)	(0.075)
Lagged Revenue	0.072***	0.221***	0.069***	0.173***
	(0.022)	(0.070)	(0.023)	(0.061)
Observations	9,058	9,058	16,451	25,509
R-squared	0.100	0.093	0.147	0.132
Firm and Year FE	Y	Y	Y	Y
Sector Specific Time Trend	Y	Y	Y	Y

*Note: FE stands for fixed effects. The outcome variable in columns 1 and 3 is logged number of procurement contracts and that in columns 2 and 4 is logged gross procurement value. Columns 1 and 2 use the precampaign subsample and columns 3 and 4 use the campaign period sample. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1*

Table A.6: Dyadic Analysis Using Alternative SOE Measures

	Procurement Number				
	08-18				13-18
	(1)	(2)	(3)	(4)	(5)
SOE	0.024***	0.024***	0.024***		
	(0.003)	(0.003)	(0.003)		
Inspection	−0.002**				
	(0.001)				
SOE*Inspection	0.018***	0.018***	0.018***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Sector-by-year FE	Y	Y	Y	N	N
Province-by-Year FE	N	Y	Y	Y	Y
Province-by-Sector FE	N	N	Y	N	N
Firm-by-Year FE	N	N	N	Y	Y
Province-by-Firm FE	N	N	N	Y	Y
N	869,271	869,271	869,271	869,271	553,784
Adjusted R^2	0.017	0.040	0.048	0.508	0.585

	Procurement Value				
	08-18				13-18
	(1)	(2)	(3)	(4)	(5)
SOE	0.104***	0.104***	0.104***		
	(0.013)	(0.013)	(0.013)		
Inspection	−0.010**				
	(0.004)				
SOE*Inspection	0.073***	0.073***	0.073***	0.016**	0.012*
	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)
Sector-by-year FE	Y	Y	Y	N	N
Province-by-Year FE	N	Y	Y	Y	Y
Province-by-Sector FE	N	N	Y	N	N
Firm-by-Year FE	N	N	N	Y	Y
Province-by-Firm FE	N	N	N	Y	Y
N	869,271	869,271	869,271	869,271	553,784
Adjusted R^2	0.017	0.033	0.039	0.365	0.414

*Note: FE stands for fixed effects. The upper panel shows the result on procurement number (logged) and the lower panel shows that on procurement value (logged). In each panel, the time frame in columns 1 – 4 is 2008–2018 and that in coulumn 5 is 2013–018. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1*

Table A.7: Prefectural Inspection Analysis

	Procurement Number	Procurement Value
	(1)	(2)
SOE	0.001***	0.004***
	(0.0002)	(0.001)
SOE*Inspection	0.002***	0.009***
	(0.001)	(0.003)
Sector-by-year FE	Y	Y
Province-by-Year FE	Y	Y
Province-by-Sector FE	Y	Y
N	8,188,678	8,188,678
Adjusted R^2	0.013	0.010

*Note: FE stands for fixed effects. *** p<0.01, ** p<0.05, * p<0.1*

Table A.8: Dydadic Analysis

	Procurement Number				
	(1)	(2)	(3)	(4)	(5)
SOE	0.015***	0.015***	0.015***		
	(0.001)	(0.001)	(0.001)		
Inspection	0.002***				
	(0.001)				
SOE*Inspection	0.013***	0.013***	0.013***	0.005***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Sector-by-year FE	Y	Y	Y	N	N
Province-by-Year FE	N	Y	Y	Y	Y
Province-by-Sector FE	N	N	Y	N	N
Firm-by-Year FE	N	N	N	Y	Y
Province-by-Firm FE	N	N	N	Y	Y
N	869,209	869,209	869,209	869,209	553,722
Adjusted R^2	0.015	0.037	0.045	0.509	0.585
	Procurement Value				
	(1)	(2)	(3)	(4)	(5)
SOE	0.069***	0.069***	0.069***		
	(0.005)	(0.005)	(0.005)		
Inspection	0.011***				
	(0.003)				
SOE*Inspection	0.059***	0.060***	0.060***	0.026**	0.024**
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Sector-by-year FE	Y	Y	Y	N	N
Province-by-Year FE	N	Y	Y	Y	Y
Province-by-Sector FE	N	N	Y	N	N
Firm-by-Year FE	N	N	N	Y	Y
Province-by-Firm FE	N	N	N	Y	Y
N	869,209	869,209	869,209	869,209	553,722
Adjusted R^2	0.014	0.030	0.036	0.359	0.406

*p < .1; **p < .05; ***p < .01

Table A.9: Profitability

VARIABLES	(1) ROA	(2)	(3) ROE	(4)
SOE*Campaign	8.28e-05	0.00120	0.00448	0.00497
	(0.00315)	(0.00331)	(0.00452)	(0.00518)
SOE	-0.00878**	-0.0124***	-0.0110	-0.0222***
	(0.00371)	(0.00313)	(0.00830)	(0.00714)
Observations	27,453	27,417	27,158	27,135
R-squared	0.031	0.071	0.021	0.060
Controls	No	Yes	No	Yes
Sector and Year FE	Yes	Yes	Yes	Yes
Sector Specific Time Trend	Yes	Yes	Yes	Yes

*Note: FE stands for fixed effects. *** p<0.01, ** p<0.05, * p<0.1*

Table A.10: Controlling Preference for SOEs

VARIABLES	(1) Procurement Number	(2)	(3) Procurement Value	(4)
SOE*Campaign	0.191***	0.191***	0.520***	0.519***
	(0.0467)	(0.0467)	(0.148)	(0.148)
SOE	0.0201	0.0201	0.145	0.145
	(0.0310)	(0.0310)	(0.106)	(0.106)
”SOE” Frequency in workreport	0.00337		0.0210	
	(0.00426)		(0.0131)	
”SOE” Frequency in workreport (log)		0.0144		0.0989
		(0.0213)		(0.0654)
Constant	-3.181***	-3.189***	-10.49***	-10.56***
	(0.301)	(0.302)	(0.878)	(0.883)
Observations	25,435	25,435	25,435	25,435
R-squared	0.145	0.145	0.133	0.133
Sector and Year FE	Yes	Yes	Yes	Yes
Sector Specific Time Trend	Yes	Yes	Yes	Yes

*Note: FE stands for fixed effects. “SOE” Frequency refers the frequency of provincial government mentioning ”state-owned enterprises” or abbreviation of ”state-owned enterprises”. *** p<0.01, ** p<0.05, * p<0.1*

Table A.11: Differences of Impacts of Government Procurement on Receivables

VARIABLES	(1) Receivables (log)	(2)	(3) Receivables Ratio	(4)
SOE*Lagged Procurement Orders (Log)	0.0263		-0.00574	
	(0.0503)		(0.00531)	
Lagged Procurement Orders (Log)	0.153***		0.0225***	
	(0.0259)		(0.00701)	
SOE*Lagged Procurement Value (Log)		0.00257		-0.00231
		(0.0185)		(0.00185)
Lagged Procurement Value (Log)		0.0460***		0.00748***
		(0.00509)		(0.00188)
Constant	-0.00208	-0.0501	0.871***	0.875***
	(1.603)	(1.600)	(0.0596)	(0.0656)
Observations	17,582	17,582	17,582	17,582
R-squared	0.450	0.449	0.268	0.270
Control	Yes	Yes	Yes	Yes
Sector and Year FE	Yes	Yes	Yes	Yes
Sector Specific Time Trend	Yes	Yes	Yes	Yes

*Note: FE stands for fixed effects. Receivables Ratio = Receivables/Business Income. Time period of Procurement Numbers and Procurement Values is from 2013 to 2018. Time period of other variables is from 2014 to 2019. Control variables include SOE, returns on assets (ROA), firm size (measured by logged total assets), and logged revenue. *** p<0.01, ** p<0.05, * p<0.1*

Table A.12: Alternative Explanation: The Sino-US Trade War

	(1)	(2)	(3)	(4)
	Exclude Year 2018		Exclude Industries Affected Most by the Trade War	
VARIABLES	Procurement Number	Procurement Value	Procurement Number	Procurement Value
SOE*Campaign	0.158***	0.370**	0.132**	0.398**
	(0.0494)	(0.158)	(0.0590)	(0.200)
SOE	0.0341	0.218*	0.0353	0.192
	(0.0358)	(0.123)	(0.0428)	(0.149)
Constant	-2.927***	-9.701***	-2.999***	-10.13***
	(0.313)	(0.932)	(0.376)	(1.123)
Observations	20,593	20,593	12,558	12,558
R-squared	0.138	0.125	0.156	0.146
Controls	Yes	Yes	Yes	Yes
Sector and Year FE	Yes	Yes	Yes	Yes
Sector Specific Time Trend	Yes	Yes	Yes	Yes

*Note: FE stands for fixed effects. Control variables include returns on assets (ROA), firm size (measured by logged total assets), and logged revenue. Information of industries affected by the trade war comes from Cai, Che and He (2022), where they generate their measurement via text analysis on the Annual report of listed companies in China. *** p<0.01, ** p<0.05, * p<0.1*

B Procurement Data Generating and Matching Process

B.1 Data Source of Government Procurement Data

We obtain government procurement data by curling the procurement announcements released on the Chinese Government Procurement website (`http://www.ccgp.gov.cn/`). There are two independent databases on the website. One is government procurement contract database. This database provides us structured data with information on both the amount and supplier of government procurement contracts. However, information provided by this database may suffer from missing data problems. First, in this database most information are provided after 2015. Second, even after 2015, data are incomplete as well. For example, in 2016 there are only about 50,000 observations in the contract database. However, according to our approach with the announcement database. There are 484,624 observations in our database in 2016.

The other database is government procurement announcements database. This database provides all kinds of announcements of government procurement. This database contains two sub-databases which are ”abstract database” and ”main content database”, respectively. The abstract database are more structured but are available only since 2013. Moreover, after we obtain the full original database of announcements, we find that numerous values in the abstract data are ”see the body of the announcement for details”. Therefore, we have to extract and analyze information based on ”main content database” for this research project.

B.2 Data Generating Process

We obtain over 10,000,000 announcements before 2019. We process the announcement headlines with regular expressions and selected the announcement texts with bid winning, transaction,or results information. We obtain 3,000,658 announcements. We then use Python to perform natural language process on the texts with bid and contract information. Specifically, we use the CPCA package to collect geographic information, including provincial, city and county levels, for the headlines of these contracts. In addition, since the original text is not structured, we perform named entity detection on the announcement text. We use the spaCy package to extract the bid information including the time and amount of the government procurement and to extract the supplier company of the procurement. The extraction success rate of machine learning algorithm is not 100% but it performs quite well. We succeed extracting names of firms in 2,525,822 announcements (about 85%) and among the above 2,525,822 announcements there are 2,133,215 announcements we can succeed extracting their amount of money(about 85%).

B.3 Matching Process

After extracting the information of procurement firms, we match the procurement firms with listed firms with both exact matching and fuzzy matching. We develop a customized fuzzy matching method based on Chinese word segmentation by first constructing a dictionary including common suffix of company names like "有限公司"(Ltd.) or "股份有限公司"(Co. Ltd.) in Chinese. We then segment companies' name and compare the differences of the core part using three indicators.

Table B.1: An Example of Fuzzy Matching

	Procurement Firms	Listed Firms
Original	沃森生物技术有限公司	云南沃森生物技术股份有限公司
Segmentation	沃森生物技术\有限公司	云南沃森生物技术\ 股份有限公司
Core Part	沃森生物技术	云南沃森生物技术

Similarity Score	Former in Latter	Latter in Former
83.86	1	0

Table B.1 presents an example: the first is the similarity score of word vector; the second is whether the core part of former column is contained in the core part of latter column; the third is whether the core part of latter column is contained in the core part of former column. In order to avoid as many omissions as possible, we keep all data of which the Former in Latter indicator is 1 or the Latter in Former indicator is 1. We manually check and drop out those samples that are incorrectly matched with the help of Industrial and commercial registration data query system provided by QICHACHA (`https://www.qcc.com/`).

C Calculation of Firm Productivity

Following Jurzyk and Ruane (2021) , our productivity measure is a total factor productivity (TFP) constructed as value-added divided by a geometric average of capital (measured as fixed asset) and labor (measured as employment), corresponding to a standard Cobb-Douglas production function.

$$Y_{i(s)} = A_{i(s)} K_{i(s)}^{\alpha_s} L_{i(s)}^{1-\alpha_s}$$

$$\text{TFPR}_{i(s)} \equiv \frac{\text{Value-added}_{i(s)}}{K_{i(s)}^{\alpha_s} L_{i(s)}^{1-\alpha_s}} = \frac{P_{i(s)} Y_{i(s)}}{K_{i(s)}^{\alpha_s} L_{i(s)}^{1-\alpha_s}} = P_{i(s)} A_{i(s)}$$

The TFP measure here is a measure of "revenue productivity" (TFPR). TFPR is different from the firm's technical efficiency (often referred to as physical productivity $A_{i(s)}$or TFPQ. Constructing TFPQ often requires further assumptions and classic methods for measuring TFPQ include OLS method, OP method (Olley and Pakes, 1992) and LP method (Levinsohn and Petrin, 2003).

Beyond all the necessary assumptions required to calculate TFPQ, the key difference between TFPQ measures and our TFPR measure is whether to calculate the input and output of a single firm or calculate the total factor productivity according to the same sector-specific factor prices. Intuitively, to get an output Y^*, a firm could choose countless combinations of K and L. However, from the perspective of certain sector, the average price of production factors reflects how firms within the sector should choose K and L to maximize output. Failure to allocate the production combination according to the factor prices will lead to the reduction of TFPR.

Therefore, our relatively simple TFPR measure reflects economic allocation efficiency. That consists with Bils, Klenow and Ruane (2021)'s argument that gaps in revenues per input (TFPR) across plants may reflect misallocation. Facing the unified factor price of the industry, do enterprises allocate resources efficiently to maximize its output? We calculate our TFPR measure with the following steps.

1. Calculation of Value-added

$$\begin{aligned}\text{Value Added}_{i(s)t} &= \text{Total Revenues}_{i(s)t} - \text{Intermediate Inputs}_{i(s)t} \\ &= \text{Total Revenues}_{i(s)t} - \text{Employment}_{i(s)t} * \text{Average urban wages}_{st}\end{aligned}$$

   where firm i in sector s in year t has $\text{Value Added}_{i(s)t}$. Data of $\text{Total Revenues}_{i(s)t}$ and $\text{Employment}_{i(s)t}$ come from Wind and data of $\text{Average urban wages}_{st}$ come from CEIC (`https://www.ceicdata.com`).

2. Calculation of Capital Share α_s

   We use fixed assets as our measure of capital, and employment as our measure of labor.

$$\alpha_s = \frac{\sum_t^T \alpha_{st}}{T - t + 1}$$

$$\alpha_{st} = \frac{RK_{st}}{RK_{st} + w_{st} L_{st}}$$

   where w_{st} is $\text{Average urban wages}_{st}$ of sector s in year t and data of w_{st} come from CEIC (`https://www.ceicdata.com`). L_{st} is sectoral employment and $L_{st} = \sum_i L_{i(s)t}$. K_{st} is sectoral fixed asset and $K_{st} = \sum_i K_{i(s)t}$. We impose a rental rate of 20% (R=0.2) following Bils, Klenow and Ruane (2021). Time period is from 2008 to 2018.

3. Calculation of TFPR α_s

$$\text{TFPR}_{i(s)t} = \frac{\text{Value-added}_{i(s)t}}{K_{i(s)t}^{\alpha_s} L_{i(s)t}^{1-\alpha_s}}$$

D Allocation Efficiency Analysis

The ex-ante analysis uses the following specifications.

Productivity$_{i(k)t} = \beta_0 + \beta_1 Campaign_t + \beta_2 X_{it-1} + \tau_{kt} + \delta_k + \epsilon_{i(k)t}$. *(Procurement Winners Sample)*

We only include firms that win at least one government procurement contract in year t in this ex-ante analysis. To measure firm productivity, we adopt logged TFPR of a firm i in year t. β_1 is our parameter of interest and it reflects the average productivity difference of the winning firms before and after the anticorruption campaign. We control the $Size$ and $Revenue$ of firm i in year $t-1$. Because of collinearity, we cannot control the fixed effect of the year but we could control the overall linear trend and the linear trend of each industry. We cluster standard errors at the firm level.

We use the following 2SLS specification to how procurement value affects firm productivity.

$$Procurement_{i(k)t} = \beta_0 + \beta_1 SOE_{i(k)t} * Campaign_t + \beta_2 SOE_{i(k)t} + \epsilon_{i(k)t}, .$$

$$Productivity_{i(k)t} = \beta_0 + \beta_1 \widehat{Procurement}_{i(k)t} + \beta_2 X_{it} + \tau_{kt} + \delta_k + \gamma_t + \epsilon_{i(k)t}.$$

where the first stage is just our baseline specification that regresses procurement value or volume on the interaction of SOE dummy and campaign dummy, and SOE dummy. In the second stage, the outcome variable, $Productivity$, is measured by logged TFPR of a firm i in year t. The treatment variable, $Procurement$, is the predicted (1) logged number and logged value of procurement contracts obtained by firm i obtains in year t. We control for the same firm covariates and fixed effects as in our baseline regressions. We cluster standard errors at the firm level.

Table D.1: Productivity of Procurement Winners

	(1)	(2)	(3)	(4)
VARIABLES	Productivity of This Year			
Campaign	-0.154***	-0.156***	-0.117***	-0.120***
	(0.0351)	(0.0350)	(0.0355)	(0.0359)
Year Trend	0.0592***			
	(0.00575)			
"SOE" Frequency in Workreport				-0.00238
				(0.00512)
Constant	-115.0***	4.305***	6.222***	6.232***
	(11.57)	(0.0301)	(0.351)	(0.353)
Observations	8,870	8,870	8,414	8,408
R-squared	0.756	0.757	0.767	0.767
	Productivity of Last Year			
Campaign	-0.0940**	-0.0947**	-0.0974**	-0.0969**
	(0.0410)	(0.0408)	(0.0404)	(0.0409)
Year Trend	0.0594***			
	(0.00691)			
"SOE" Frequency in Workreport				0.000605
				(0.00520)
Constant	-115.5***	4.226***	6.304***	6.298***
	(13.91)	(0.0342)	(0.380)	(0.383)
Observations	8,186	8,186	8,186	8,180
R-squared	0.715	0.718	0.724	0.724
Control	No	No	Yes	Yes
Year FE	No	No	No	No
Sector FE	Yes	Yes	Yes	Yes
Sector Specific Time Trend	No	Yes	Yes	Yes

*Note: FE stands for fixed effects. "Campaign" is a dummy variable which equals one if variable year is larger than 2012. The coefficients of variable "Campaign" are all negative if we replace the outcome variable with "ROA of Last Year". Control variables include the Size and Revenue of a firm in year t-1. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1*

Table D.2: Impacts on Firm Productivity

	(1)	(2)	(3)	(4)
	2SLS		Reduced Form	
VARIABLES	Productivity (log)			
Procurement Number (log)	-0.323**			
	(0.149)			
Procurement Value (log)		-0.0960**		
		(0.0450)		
SOE*Campaign			-0.0899**	-0.0897**
			(0.0407)	(0.0407)
SOE			0.00540	0.00485
			(0.0316)	(0.0316)
"SOE" Frequency in workreport				0.00456
				(0.00309)
Constant	-48.40	-47.41	5.418***	5.399***
	(89.49)	(89.77)	(0.210)	(0.210)
Observations	22,267	22,267	22,267	22,261
R-squared	0.755	0.757	0.791	0.791
Control	Yes	Yes	Yes	Yes
Sector and Year FE	Yes	Yes	Yes	Yes
Sector Specific Time Trend	Yes	Yes	Yes	Yes

*Note: FE stands for fixed effects. Control variables include the Size, Revenue and ROA of a firm in year t-1. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1*

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